AUTOMATIC LUMBAR VERTEBRAE SEGMENTATION IN FLUOROSCOPIC IMAGES VIA OPTIMISED CONCURRENT HOUGH TRANSFORM

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Abstract- **Low back pain is a very common problem in the industrialised countries and its associated cost is enormous. Diagnosis of the underlying causes can be extremely difficult. Many studies have focused on mechanical disorders of the spine. Digital videofluoroscopy (DVF) was widely used to obtain images for motion studies. This can provide motion sequences of the lumbar spine, but the images obtained often suffer due to noise, exacerbated by the very low radiation dosage. Thus determining vertebrae position within the image sequence presents a considerable challenge.**

In this paper, we show how our new approach can automatically detect the positions and borders of vertebrae concurrently, relieving many of the problems experienced in other approaches. First, we use phase congruency to relieve difficulty associated with threshold selection in edge detection of the illumination variant DVF images. Then, our new Hough transform approach is applied to determine the moving vertebrae, concurrently. We include optimisation via a genetic algorithm as without it the extraction of moving multiple vertebrae is computationally daunting. Our results show that this new approach can indeed provide extractions of position and rotation which appear to be of sufficient quality to aid therapy and diagnosis of spinal disorders.
Keywords – **Low back pain, DVF, phase congruency, genetic algorithm, Hough transform**

I. INTRODUCTION

A. Low Back Pain

The spine constitutes the central axis of the human body and can be divided into four parts: the cervical, thoracic and lumbar spine and the sacroiliac region. The lumbar spine is designed to bear considerable loads and provides truncal mobility. It is the main area where low back pain occurs. However, the understanding of the low back pain is limited by the structural complexity of the lumbar spine and the difficulty of *in vivo* experiments because the lumbar spine is particularly difficult to access.

Low back pain and its associated disability have appeared to escalate with time despite the considerable technical advances in diagnosis, treatment and rehabilitation. The cost of low back pain is enormous. For example, it has been estimated that chronic low back pain annually results in 225,000 to 300,000 lumbar surgeries and an estimated direct and indirect medical cost of $75 to $100 billion in the U. S. [1]. In the U. K., the situation is similar: it costs billions of pounds annually and more and more attention has been paid to low back pain in the last 25 years mainly because of this large cost [2].

There are, as yet, no well-accepted standards to determine causes of low back pain. Many people consider non-specific low back pain to be caused by abnormal motion and consequently many attempts have been made to find ways to define the relationships between motion and low back pain.

An important mechanical cause of low back pain is spinal instability which, indeed, might be one of the most common causes. It is estimated that 20-30 percent of low back pain patients have spinal instability [3]. It is often held that instability may cause abnormal movement and thus study of spinal movement could help in its definition and may benefit diagnosis and clinical surgery. In this study, radiographic methods have been widely used in obtaining data [4, 5]. In addition to these, some non-radiographic effort has been devoted to describing the relationship between low back pain and motion patterns [6, 7].

Spinal instability has not been without controversy. Mechanical disorders can be described by joint kinematics and knowledge of the forces acting on the structures involved. As the forces exerted on the lumbar spine are difficult to measure *in vivo*, clinical studies of spinal biomechanics have to focus primarily on joint kinematics. In spinal motion analysis, different parameters are used to describe the kinematics [8].

B. Digital Videofluoroscopic Imaging

In spinal data acquisition, routine imaging techniques have proved to be unsuitable. Due to the high radiation dosage, only a limited number of static images can be obtained using plain X-rays, usually in the neutral position and at the extreme positions of mobility. Consequently, it is not possible to determine the intermediate states or to describe the motion as the spine moves from flexion to extension. Computerised topography (CT) cannot yield movement information since it requires the patient to be as stationary as possible during image acquisition whilst magnetic resonance imaging (MRI) is not yet sufficiently fast in image acquisition for motion analysis.

To overcome these problems, a DVF imaging technique was introduced by Breen and Allen et al. in 1987 [9] and has undergone considerable refinement. With this technique, a series of dynamic frames of spinal motion can be captured with a lower X-ray dosage than that required for a single plain X-ray plate of the lumbar spine. A typical DVF image of the lumbar spine is shown in Fig. 1. This was obtained from a study of passive motion in which the subject lay on an articulated table and was moved passively at a controlled rate.

C. Previous Landmark Locating Methods

In spinal motion study, it is essential to locate the landmarks which can be used to determine the positions of the vertebral bodies. This work was originally achieved

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manually and consisted of locating, typically, the corners of the vertebrae as anatomical landmarks. However, it is difficult to place markers exactly on the vertebral corners and furthermore, repeatability cannot be assured. Panjabi et al [10] discussed errors that can arise when manually marking X-ray images of the spine.

Figure 1 Lateral DVF image of the lumbar spine

Several automatic approaches based on correlation have been developed to overcome these problems. Template matching methods [11, 12] were proposed but these may suffer when out-of-plane motion is evident or when occlusion occurs. Other computer vision techniques have also been applied to vertebrae extraction [13, 14], but require an excessive amount of training data. The latter method [14] is a version of the active contour (or snake). One weakness of a snake is that it depends on appropriate initialization of parameters. Moreover, snakes cannot solve the correspondence problems whereby shapes found might differ between frames because of occlusion or noise effects. Consequently, errors may be generated and would be propagated to the computation of spine kinematics.

In this paper, we propose a method in which a genetic algorithm (GA) is combined with the Hough transform (HT). It can represent non-analytical shapes continuously by using Fourier descriptors (FDs), and thus can approximate the model without distortion. By using a GA to search the Hough spaces, multiple objects can be found (here there are five lumbar vertebrae) within the same frame simultaneously and false peaks can be avoided by considering the intrinsic relationship between these vertebrae. This approach was applied to several DVF image frames and the results are encouraging as shown in below.

II. The Hough Transform

The Hough transform [15] has become one of the most powerful approaches in computer vision. It has found application in a wide variety of problems in machine vision. Two comprehensive surveys [16, 17] of the HT give much evidence of its attributes.

The philosophy of the HT is a mapping from geometric features of edge pixels in an image to a multi-dimensional space. Aguado et al. [18] gave the most elegant definition of the HT based on the Principle of Duality. Sklansky [19] proved that the HT can provide a result equivalent to that derived by template matching but with less computational effort. The HT also inherits advantages such as immunity to noise and occlusion.

The generalised HT (GHT) was first introduced by Ballard to extract arbitrary shapes [20]. In the GHT, the model shape is represented by an R-table, which is a discrete lookup table based on its edge information. When the model is scaled or rotated, there can be problems with aliasing and rounding. Distortions are inevitable when working with discrete representations, as in digital computers. This problem was overcome in an adaptation of the GHT [21] where FDs were used to represent the model shape. This description gives a continuous representation at multiple scales without the aliasing problems of the R-table.

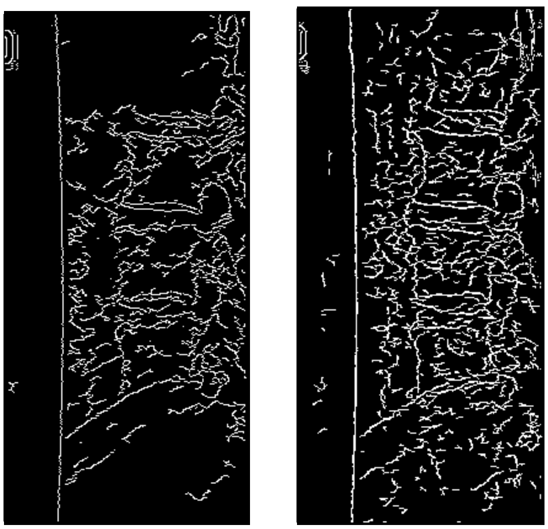
These methods were originally designed to extract single object, separately. Therefore, for multiple objects, they could only be extracted in sequential stages. However, doing this isolates the intrinsic relationships among these objects that can be very useful in extraction. For example, during spine motion, vertebrae are constrained by the physical structure. It might be possible to design a model to include all these objects, but the dimensions of the Hough space could be excessively large. As we know, for a two-dimensional object, at least three parameters (rotation and translation in x and y directions about the model) are needed to describe its pose and there will be fifteen dimensions for five objects. Furthermore, there is a possible range for each parameter and this range is discretised according to the resolution during forming Hough space. Assuming ten values for each parameter implies a 10^{15} search space. The actual space in practice is even larger than this, so traditional exhaustive searches will be impractical for so large scale.

In an attempt to conquer this problem, we have combined GA with the HT. The GA is a popular method in optimisation now and can be used to improve the search procedure. The process of the GA involves four major steps: namely, initialization, reproduction, crossover and mutation. The principle of the GA is the natural phenomenon of "survival of the fittest". Limited by space, we will not discuss it in detail here and the reader is referred to the extensive literature on its implementation and advantages [22]. By introducing a GA into the HT, it not only can solve the problem of the complexity of exhaustive searching approaches, but can also make it possible to improve the performance by considering the relationships among objects in the fitness function.

III. Results

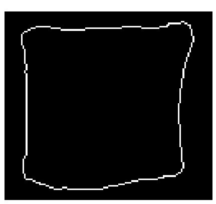
Edge information is a prerequisite to the implementation of the HT. As we discussed earlier, the quality of DVF images is poor. For edge detection, the Canny operator is most often used and is regarded as optimal. However, it cannot provide good results on DVF images of the lumbar spine, especially in the L1 and L5 areas. This might be caused by the uneven brightness and poor contrast within a single DVF image. Furthermore, there is difficulty in selecting optimal thresholds manually for a large database in order to obtain the best edge results. Here, we have used phase congruency [23] and the results suggest that it is appropriate. Different from Canny and other gradient-based methods, it utilizes the fact

that the feature points are perceived at points in an image where the Fourier components are maximally in phase. It is a dimensionless quantity and is invariant to changes in image brightness and contrast. Furthermore, it provides an absolute measure of the significance of feature points, and thus allows for a universal threshold that can be applied over wide classes of images. As such, difficulty in selecting a threshold for a whole image with uneven brightness, like DVF images, can be solved. Fig. 2 shows a comparison between Canny and phase congruency where the source image is the central area of Fig. 1. Visually, phase congruency can provide better edge information and in particular there is large improvement in boundary detail in the region of L1 and L5.

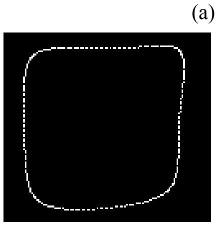


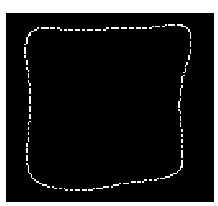
(a) Results with Canny (b) Phase congruency

Figure 2 Comparisons between Canny and Phase Congruency

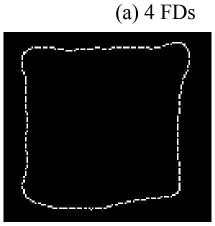


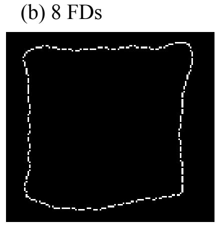
(a) Original curve





(a) 4 FDs (b) 8 FDs





(c) 16 FDs (d) 32 FDs

Figure 3 Curve and its reconstruction with different FDs.

At present the model shapes were obtained manually, but might be automatically generated in future. FDs were then derived from the chain code that can be easily obtained from the model shape [24]. With more harmonics, the reconstruction becomes increasingly close to the model. However, the total number of harmonics should conform to the sampling theorem. That is, the possible values for number of harmonics should be integers between one and the half of the sampling rate. Fig 3 (a) shows a closed curve and the rest of Fig. 3 are its reconstructions with different harmonics. In our approach, sixteen FDs were used to represent the model.

The core of the HT is how to form the Hough space. In our study, only rotation and translations in the x and y directions were considered. Thus the Hough space for each vertebra is three-dimensional. Each edge point will vote in this array and the parameters can be determined by locating the maximum in this array.

As discussed earlier, a GA was used to extract five vertebrae concurrently by looking for the peak values. For five vertebrae, there are fifteen parameters altogether and each parameter is represented using six bits, so the length of a chromosome is 90 bits. After trials, the population number was set to 100. A two-point crossover is used and its probability is 0.95. The mutation probability is 0.015. The program terminates after 2000 generations. In fact, the fitness value often converged within this value. Initialization is implemented via random numbers.

The fitness function is constructed as the sum of the Hough values corresponding to five vertebrae and the penalty constraints on positions. These constraints are used to maintain the distances between the neighboring vertebral centers are within certain range according to the physical structure of the lumbar spine. This can help to avoid false peaks caused by ambiguous edge information (especially for extraction of L1 and L5). Fig. 4 shows the fitness change against generation number in one example. After extraction, we superimpose the results on the original image for an intuitive observation. Visually, the results appear very promising and one frame is shown in Fig. 5. Fig. 6 shows the moving patterns of the lumbar spine when moving from neutral posture to extension position.

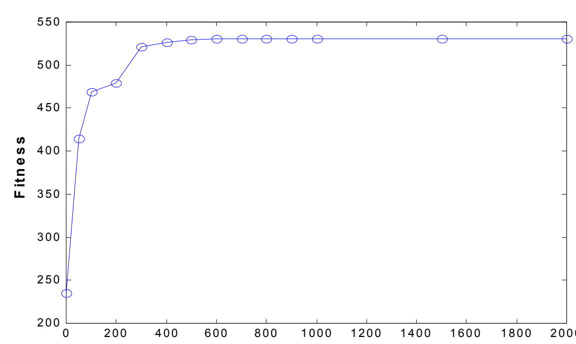


Figure 4 Fitness change *vs.* number of generation.

Figure 5 Extraction results of one DVF image.

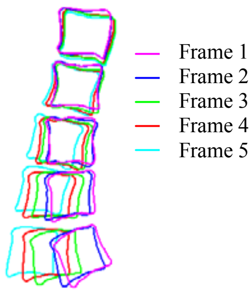


Figure 6 Extraction results of multiple frames.

IV. Conclusions and Future Work

In this paper, we show how the optimized concurrent HT can be used to locate five lumbar vertebrae simultaneously from DVF images. The results are very promising. A major advantage is that it can consider the relationships between objects and thus it can help to avoid false extraction

In the current algorithm, only the relative positions between vertebrae were considered, but there is much temporal information in a motion sequence that can be used, for example, the motion parameters for each vertebra will not change abruptly because of the constraints from ligaments and muscles. Our future work will consider incorporating the temporal information into our present approach to form a spatial-temporal HT and the design of an appropriate fitness function. The new approach will be particularly attractive for coping with medical image sequences of poor quality.

Based on the results from our study, kinematic parameters of the lumbar spine can be easily obtained. Kinematics of the lumbar spine will be another focus of the future work and this should provide clinicians with valuable information for diagnosis of spinal disorders.

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